Enhanced cloud/snow identification in snow mixed vegetation/soil areas based on machine learning techniques

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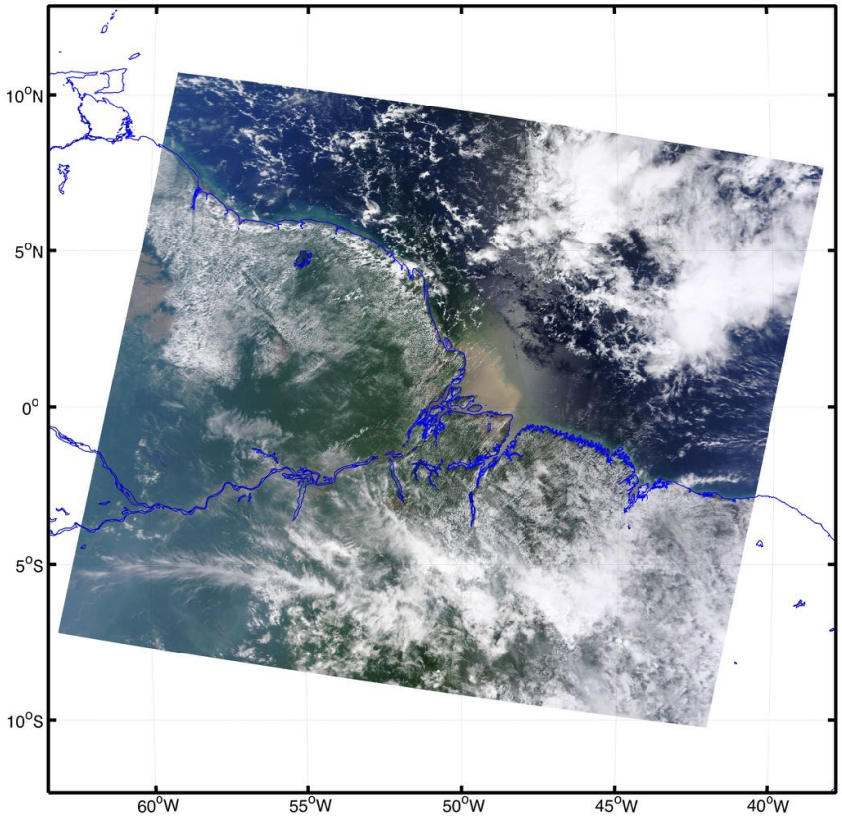
Clouds and snow detection in remote sensing

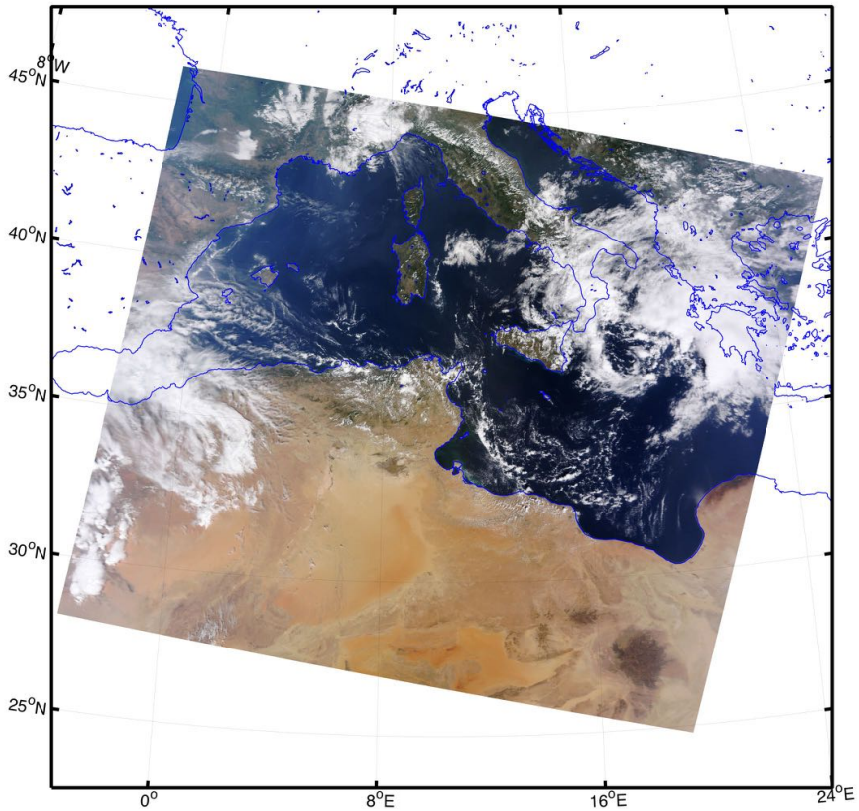
Earth image from NASA's Moderate-resolution imaging spectroradiometer (MODIS) sensor on July 11, 2005.

Clouds over vegetation and other land types

South America

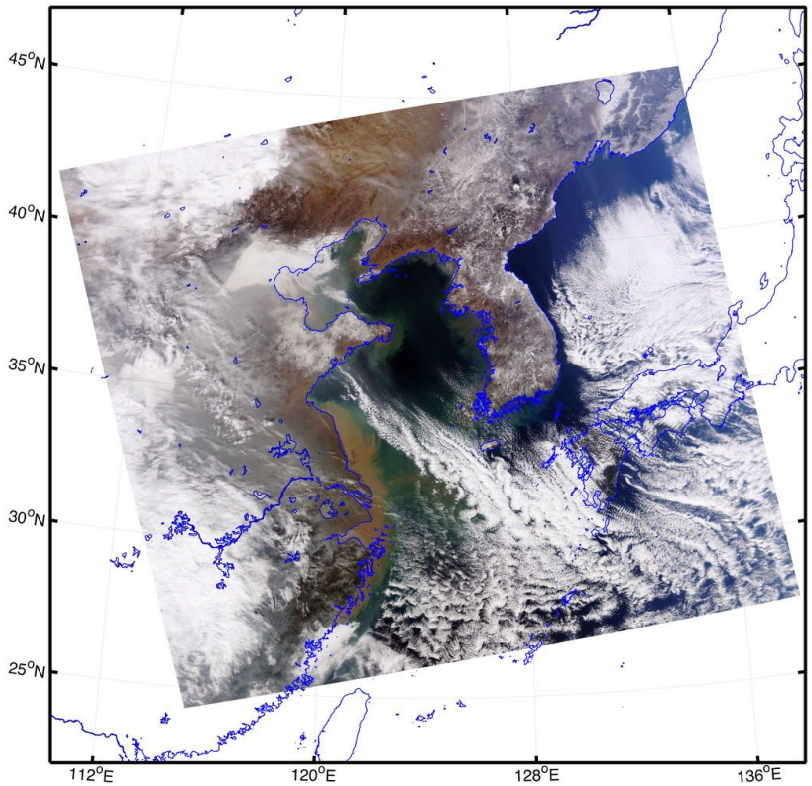


Sahara

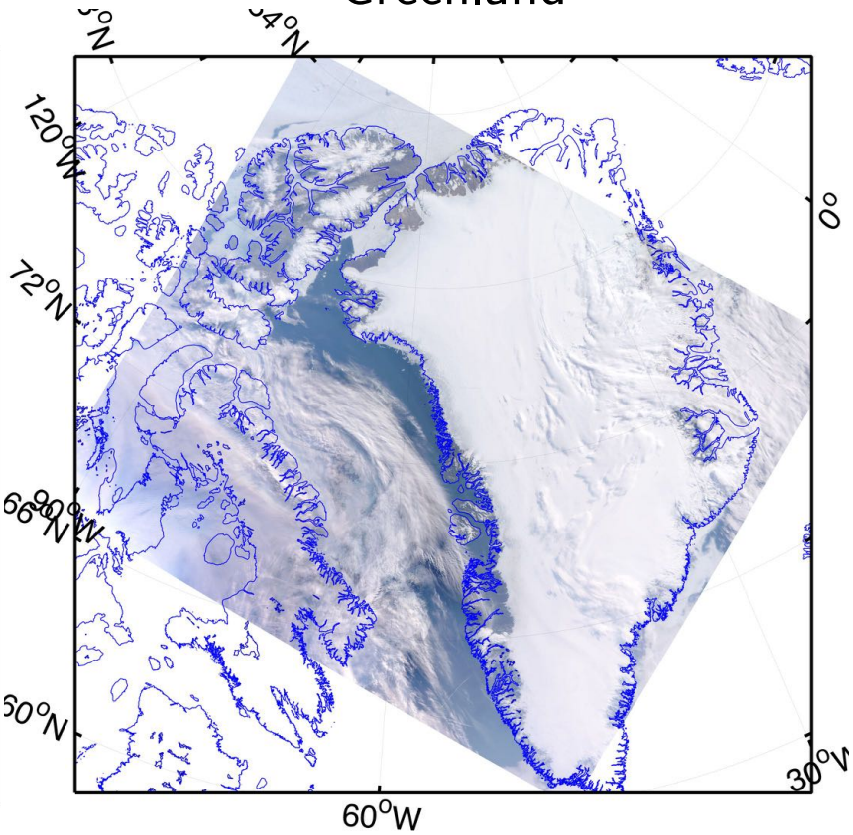


Clouds over bright backgrounds (snow and ice)

East Asia



Greenland



Clouds over bright backgrounds (snow and ice)

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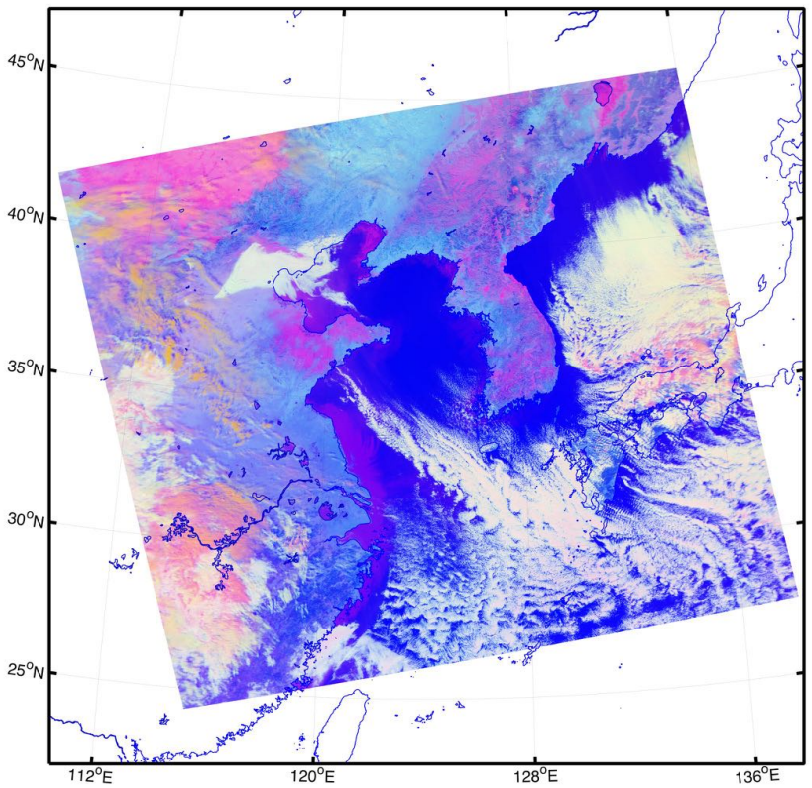
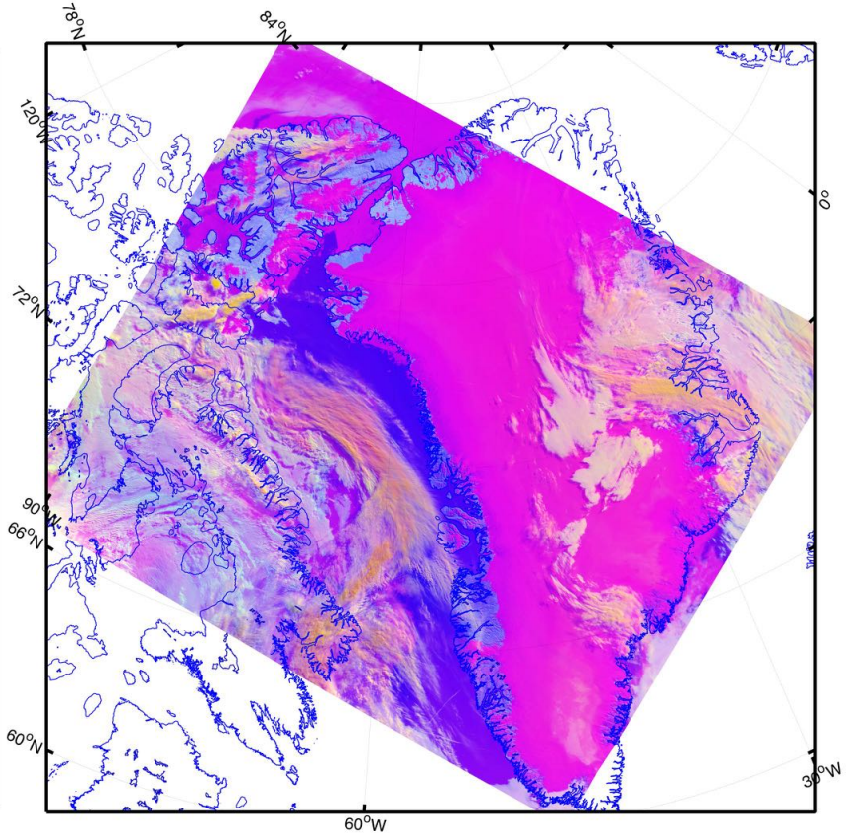


Greenland



False color RGB with R: 0.645 μm; G: 2.13 μm; B: 10.8 μm brightness temperature.

Methodology

- Combination of fixed or dynamic threshold tests.
- Use information from reflectance (VIS, NIR, SWIR) and thermal (TIR) channels.
- **Detect possible snow covered area** is important.

NDSI based snow detection

Indexes for mapping snow cover using VIS and SWIR data were developed in the mid-1970s. The NDSI (Normalized Difference Snow Index) term was first coined by [Hall et al., 1995] and used to map snow using MODIS. Prior to that, [Dozier, 1987, Dozier, 1989] used a VIS/SWIR index algorithm to map snow using Landsat data. The NDSI is defined as:

$$NDSI = \frac{R_{VIS} - R_{SWIR}}{R_{VIS} + R_{SWIR}}$$

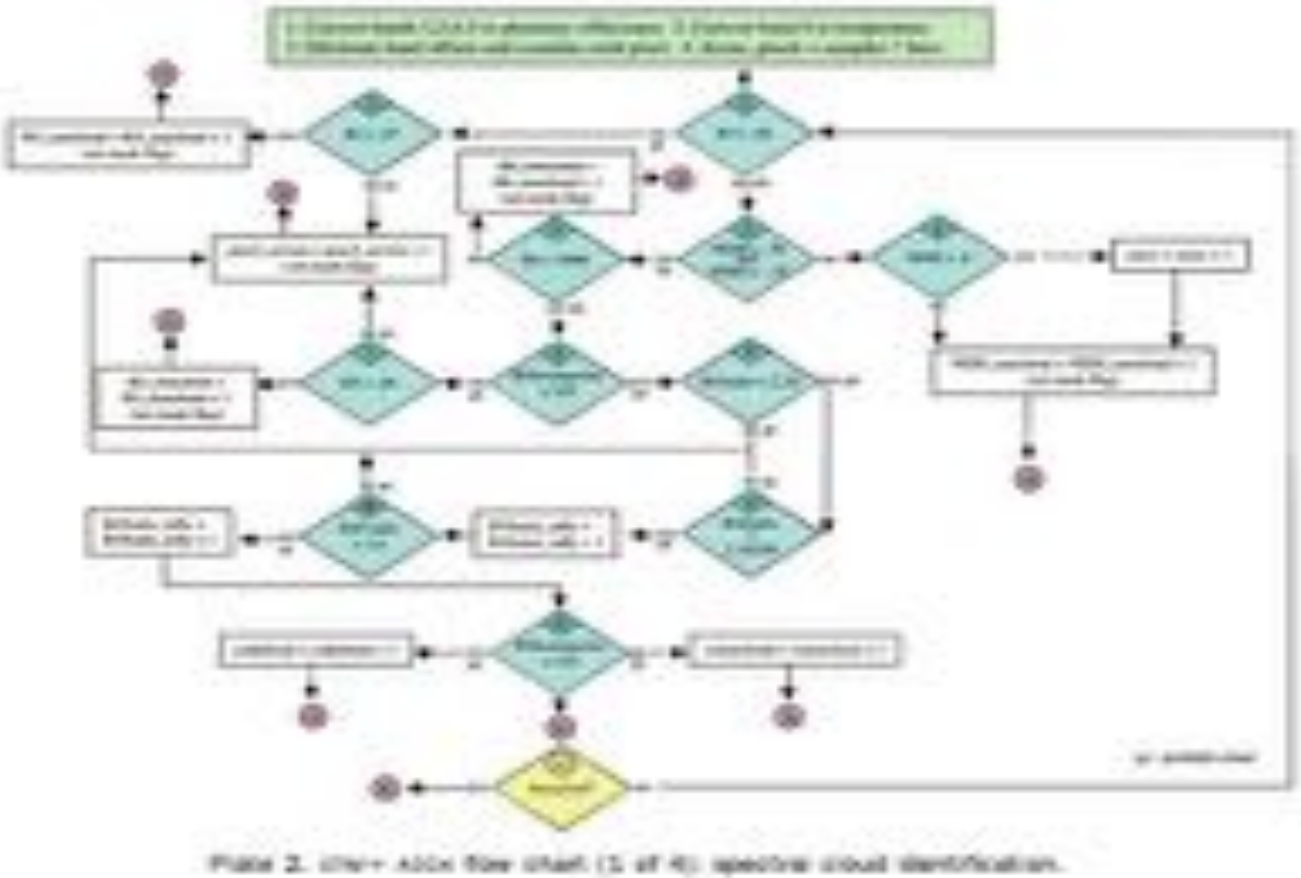
A fixed threshold (e.g. NDSI > 0.4) is typically used to detect possible snow-covered pixels.

Threshold tests - the MOD35 algorithm

Test/Bit #	Day Ocean	Night Ocean	Day Land	Night Land	Day Snow/Ice	Night Snow/Ice	Day Coast	Day Desert	Polar Day	Polar Night
BT_{11} 13	✓	✓								
BT_{11-12} 14	✓	✓	✓	✓	✓	✓	✓	✓		
BT_{6-7} 15	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$R_{1.38}$ 16	✓		✓		✓		✓	✓	✓	
$BT_{3.9}$-BT_{12} 17				✓		✓				✓
BT_{11}-BT_{12} 18	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
BT_{11}-$BT_{3.9}$ 19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$R_{0.66}$, $R_{0.87}$ 20	✓		✓				✓	✓		
$R_{0.66}$ 20								✓		
$R_{0.87}/R_{0.66}$ 21	✓							✓		
$BT_{3.9}$-BT_{11} 22				✓		✓				✓
$BT_{4.4}$-$BT_{3.9}$ 23	✓	✓								
Sfc. Temp. 27	✓	✓		✓						
$BT_{8.6}$-BT_{11} 29		✓								
BT_{11} Var. 30		✓								

Threshold tests used in MOD35 algorithm
[Ackerman et al., 1998, Ackerman et al., 2010].

Threshold tests - the ACCA algorithm

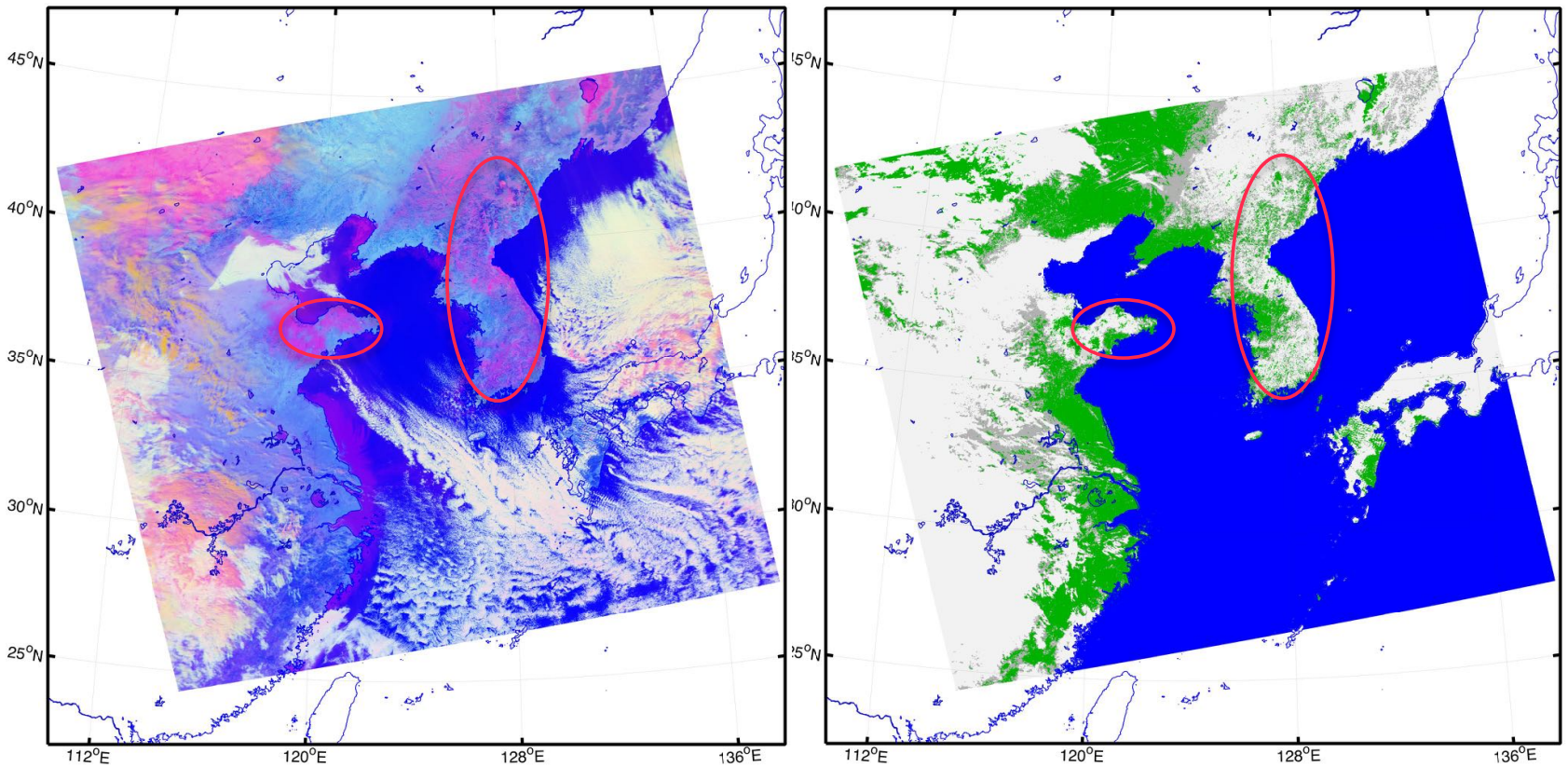


Flowchart (1 of 4) of the Automated Cloud Cover Assessment (ACCA) algorithm [Irish et al., 2006] for the Landsat ETM+ sensor.

Challenge: snow and snow mixed with vegetation areas

False color RGB image

MYD35 cloud mask



Aqua MODIS image over East Asia, Jan. 24, 2003. Color scheme of cloud mask figure: white/grey - clouds, blue - ocean, green - land. Only clouds detected over land areas are shown.

Limitations of threshold based methods

- A large number of tests makes the logic very complicated and different tests may produce conflicting results.
- Fixed threshold settings make it difficult to handle complex surface mixing situations, especially when the surface is partially covered by snow.
- The accuracy of snow detection affects that of cloud detection because it determines the test combinations applied on each pixel.
- A relatively large number of satellite channels are needed to detect clouds as well as snow/ice (e.g. MOD35 uses 10 reflectance bands and 9 IR bands).
- Tests using thermal IR channels are not reliable over snow-covered areas, especially over Greenland and Antarctica due to frequent temperature inversions.

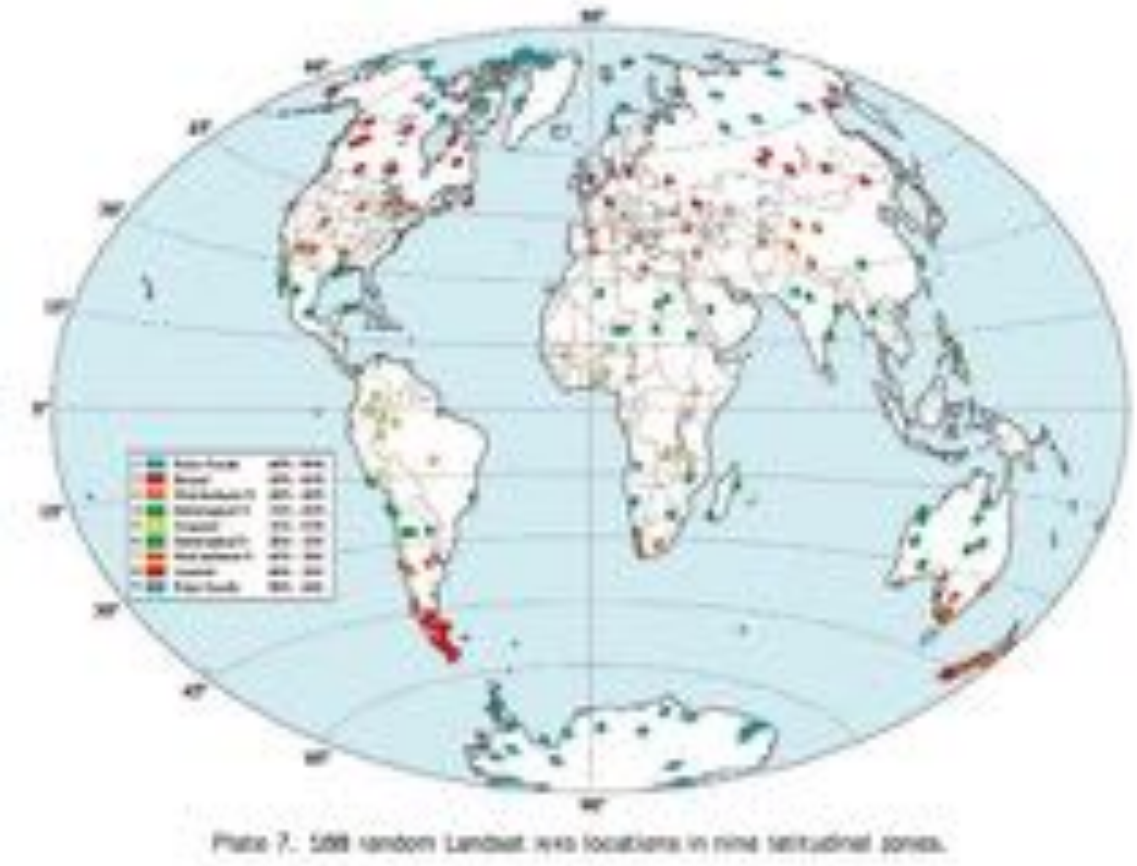
Previous attempts using machine learning techniques

From the 1990s machine learning techniques (MLTs) are being used to detect clouds. Due to the complexity of the problem, **supervised machine learning techniques** are usually employed. These methods include:

- support vector machine (SVM)
- artificial neural network (ANN)
- logistic regression (LR)

High quality training data sets are the key to achieve high performance using machine learning algorithms.

How to get training data?



The ACCA reference data set [Irish et al., 2006], one of the most commonly used validation/training data sets for cloud mask algorithms, is a **human identified data set**. It contains 212 scenes from 188 Landsat World Reference System (WRS) stations.

Limitations of human identified training data set

- **Difficult to prepare** (need humans to identify millions of pixels).
- **Difficult to achieve full coverage** of solar/viewing geometries as well as different geolocations.
- **Difficult to account for seasonal land cover changes**, especially during the snow fall events.
- **Difficult to apply to a different sensor** due to sensor spectral characteristic changes.

New Approach: Simulation + machine learning

Can we use a **simulated** TOA reflectance dataset to train machine learning algorithms?

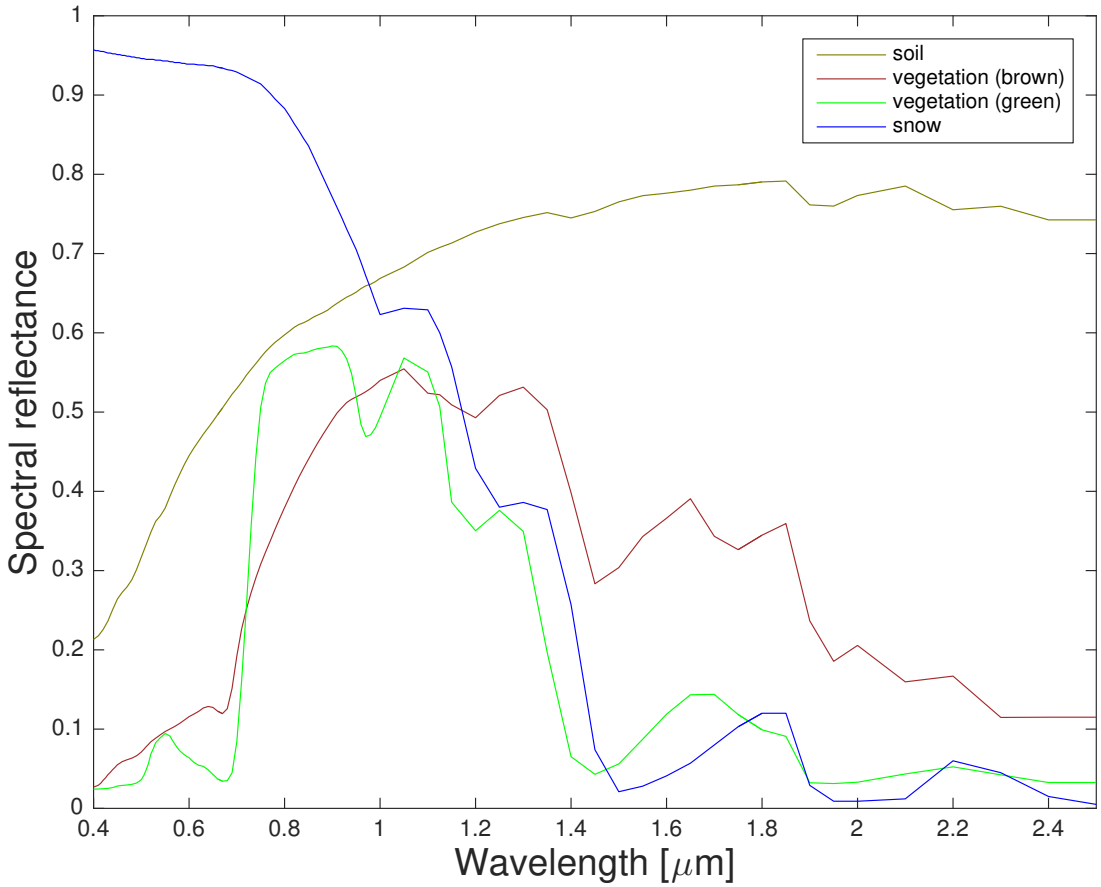
If possible, then we would have the following advantages over a human-identified dataset:

- There is no need for humans to identify hundreds of images with millions of pixels, which greatly saves human effort.
- The training dataset can cover the full range of possible solar/viewing geometries.
- Easy to apply to different sensors; only new training datasets are needed.

The biggest challenge in building a simulated dataset, is to **simulate complicated land surface types and account for various possible mixing conditions**.

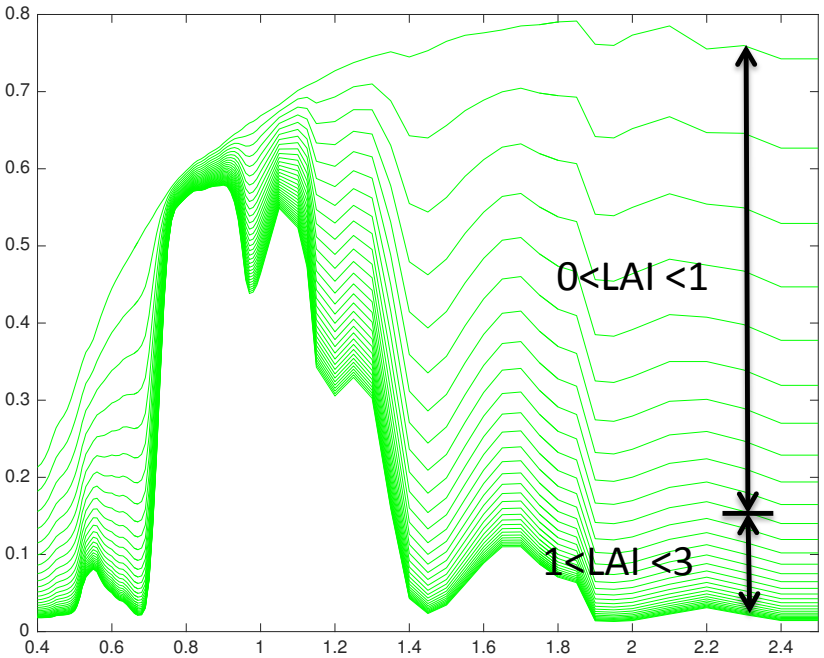
How do we simulate complicated land reflectance?

Available land surface reflectance models, such as the Soil-Leaf-Canopy (SLC) model (Verhoef et al., 2007), can be used in **radiative transfer models (RTMs)** to simulate Top of Atmosphere (TOA) reflectances for an atmosphere overlying different land surfaces.

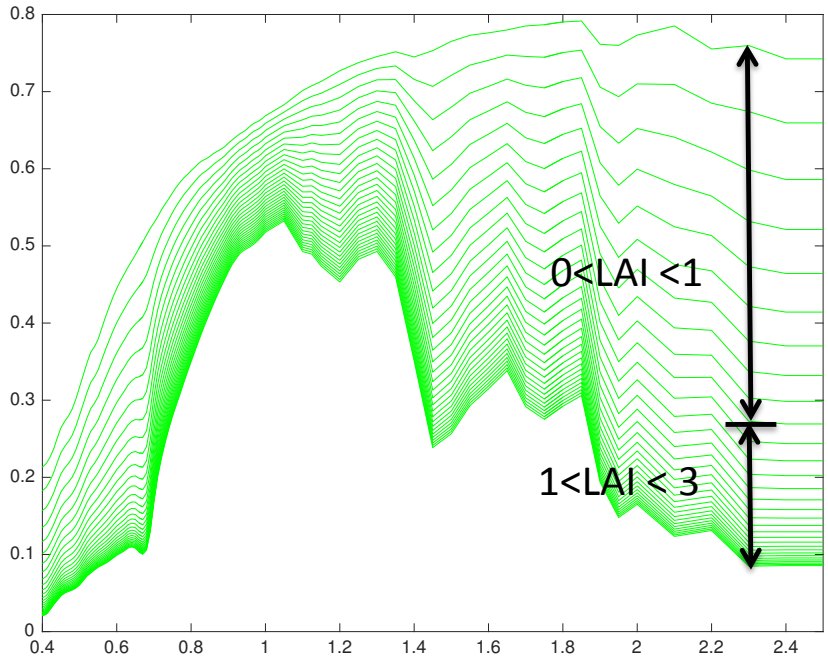


Changing surface parameters

Green vegetation



Brown vegetation



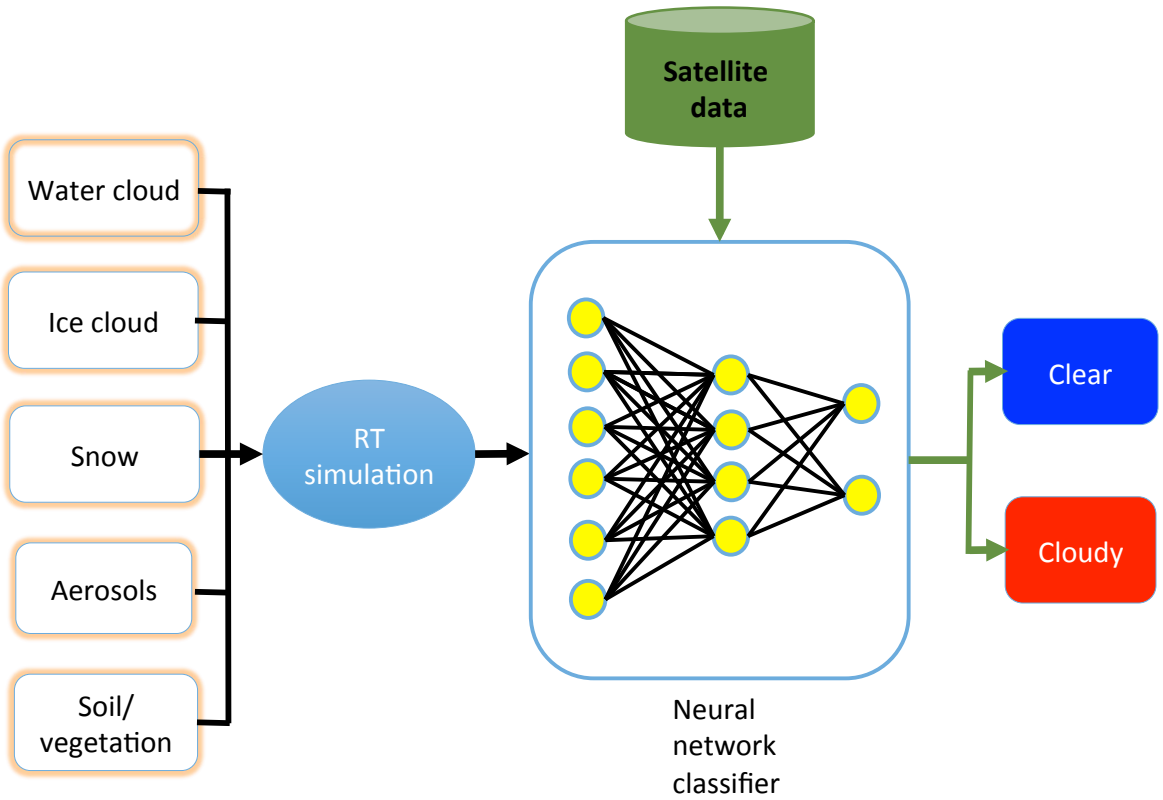
Sub-pixel reflectance mixing

In order to better handle the case of fractional snow cover, we assume the following linear mixing rule for the reflectance of pixels with snow fraction, f:

$$R_{\mathrm{mix}} = (1 - f) \times R_{\mathrm{land}} + f \times R_{\mathrm{snow}}.$$

By randomly changing the snow fraction f and different snow/land parameters, we can simulate the TOA reflectance of different snow-mixed-vegetation/soil cases.

Neural network based cloud detection



- Over 10 million clear-sky and cloudy cases as the input.
- A simple classification neural network with one hidden layer.

Training for different sensors

The new neural network based algorithm can be configured (trained) for different numbers of channels. A 6-channel configuration was created and tested for Aqua MODIS and a 3-channel configuration for AVHRR-3.

Sensor	VIS chan (μm)	NIR chan (μm)	SWIR chan (μm)
3-channel	0.66	0.86	2.13
6-channel	0.47, 0.55, 0.66	0.86	1.24, 2.13

Image based results: snow-mixed vegetation/soil area

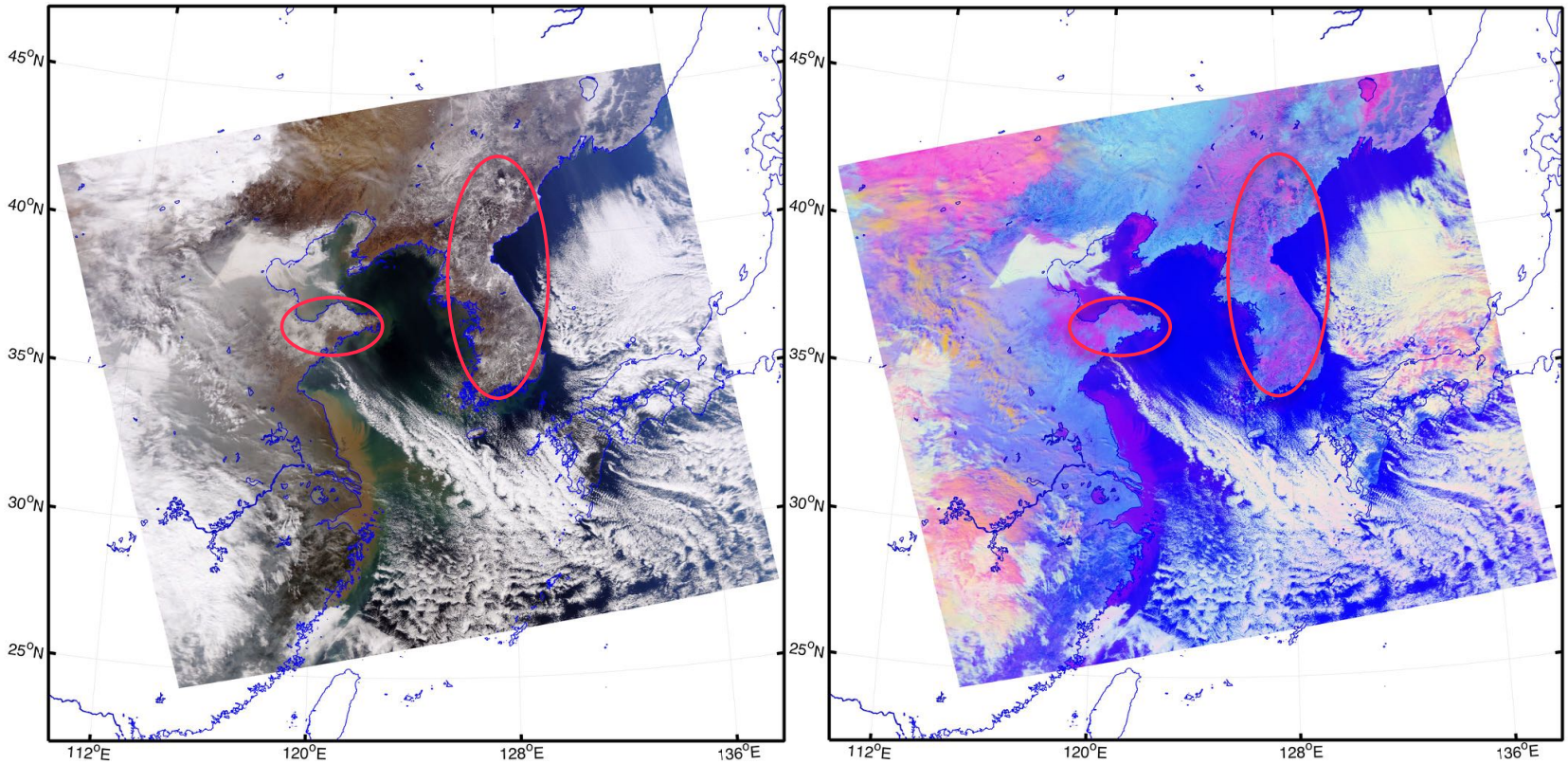
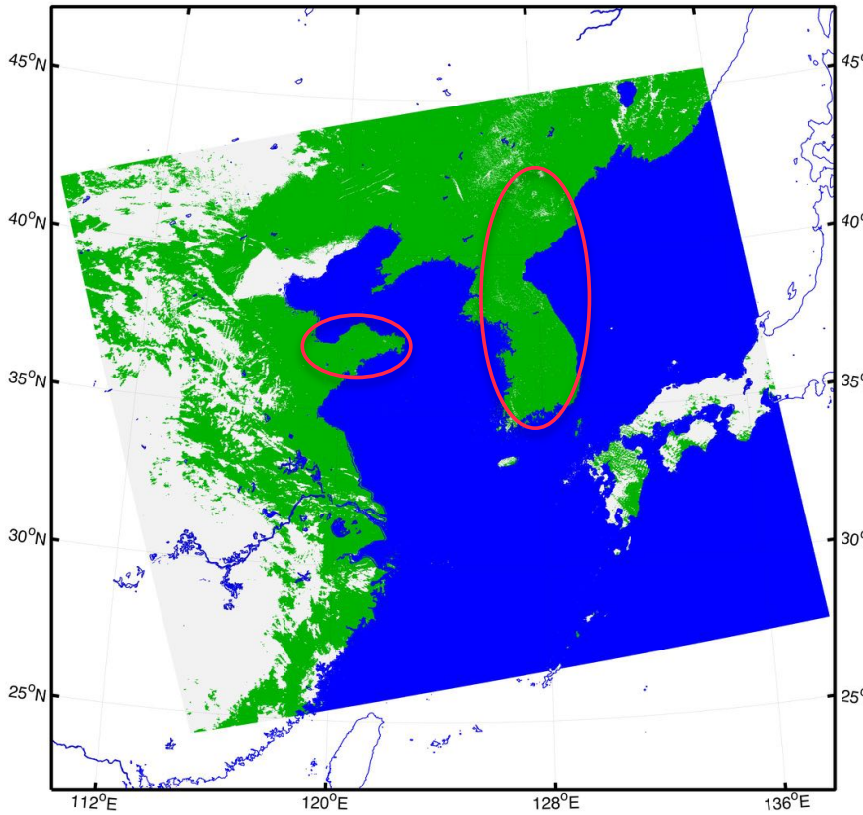


Image based results: snow-mixed vegetation/soil area

SCM cloud mask



MYD35 cloud mask

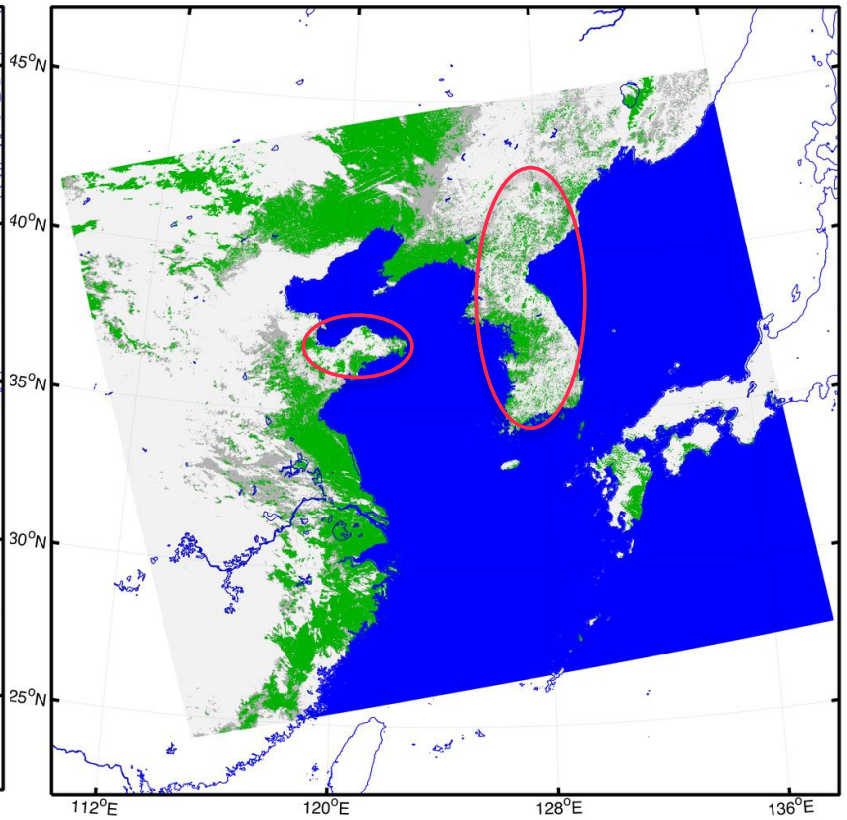


Image based results: snow-mixed vegetation/soil area

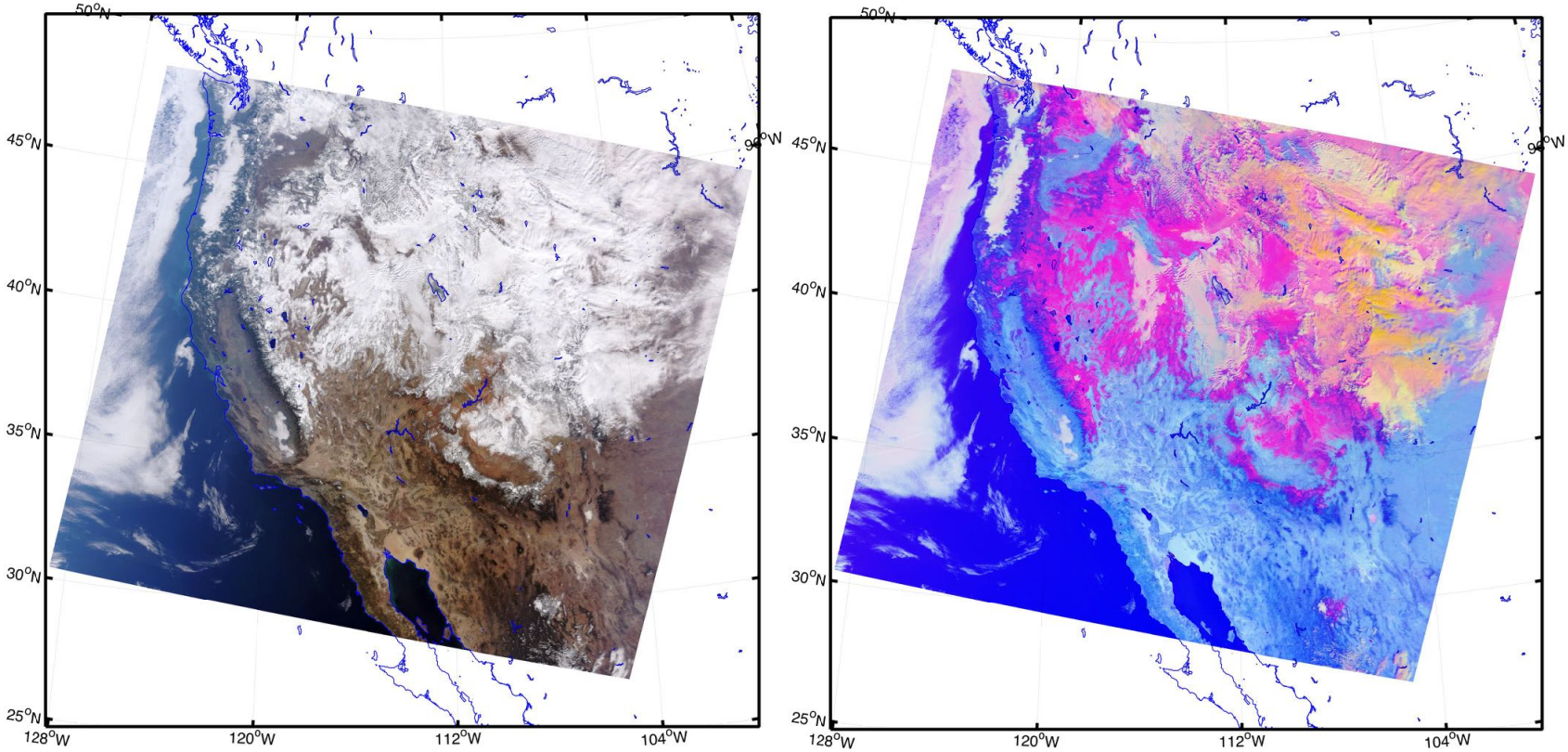
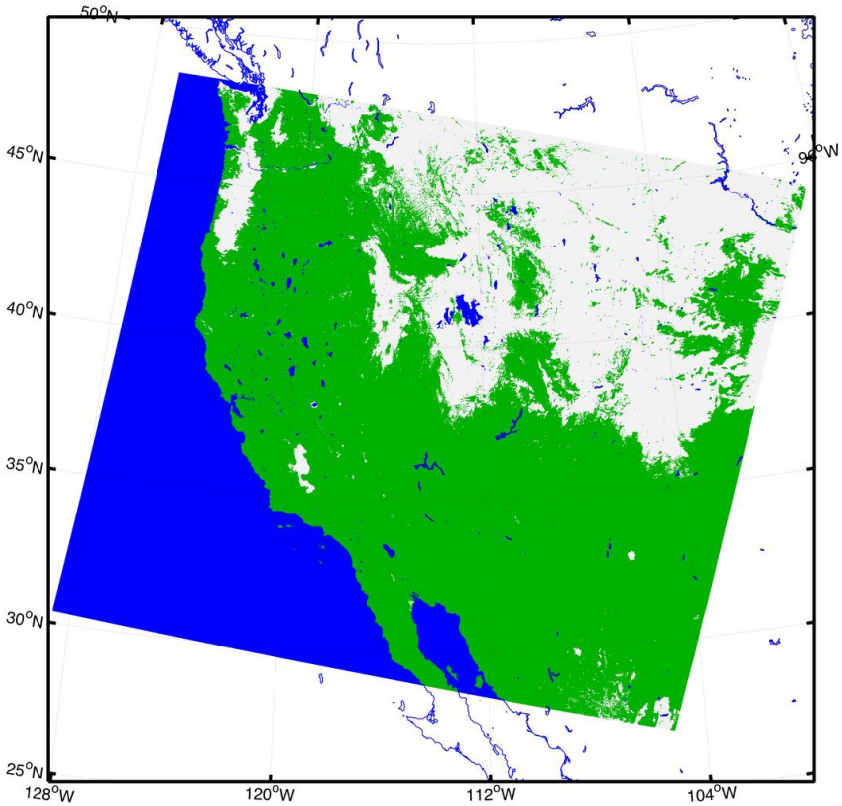
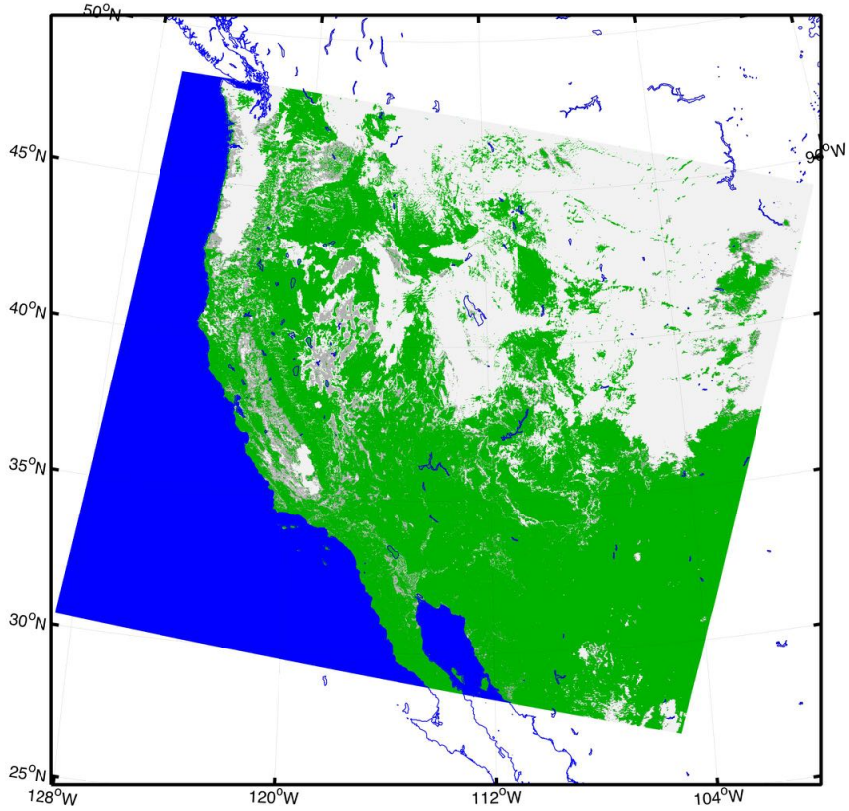


Image based results: snow-mixed vegetation/soil area

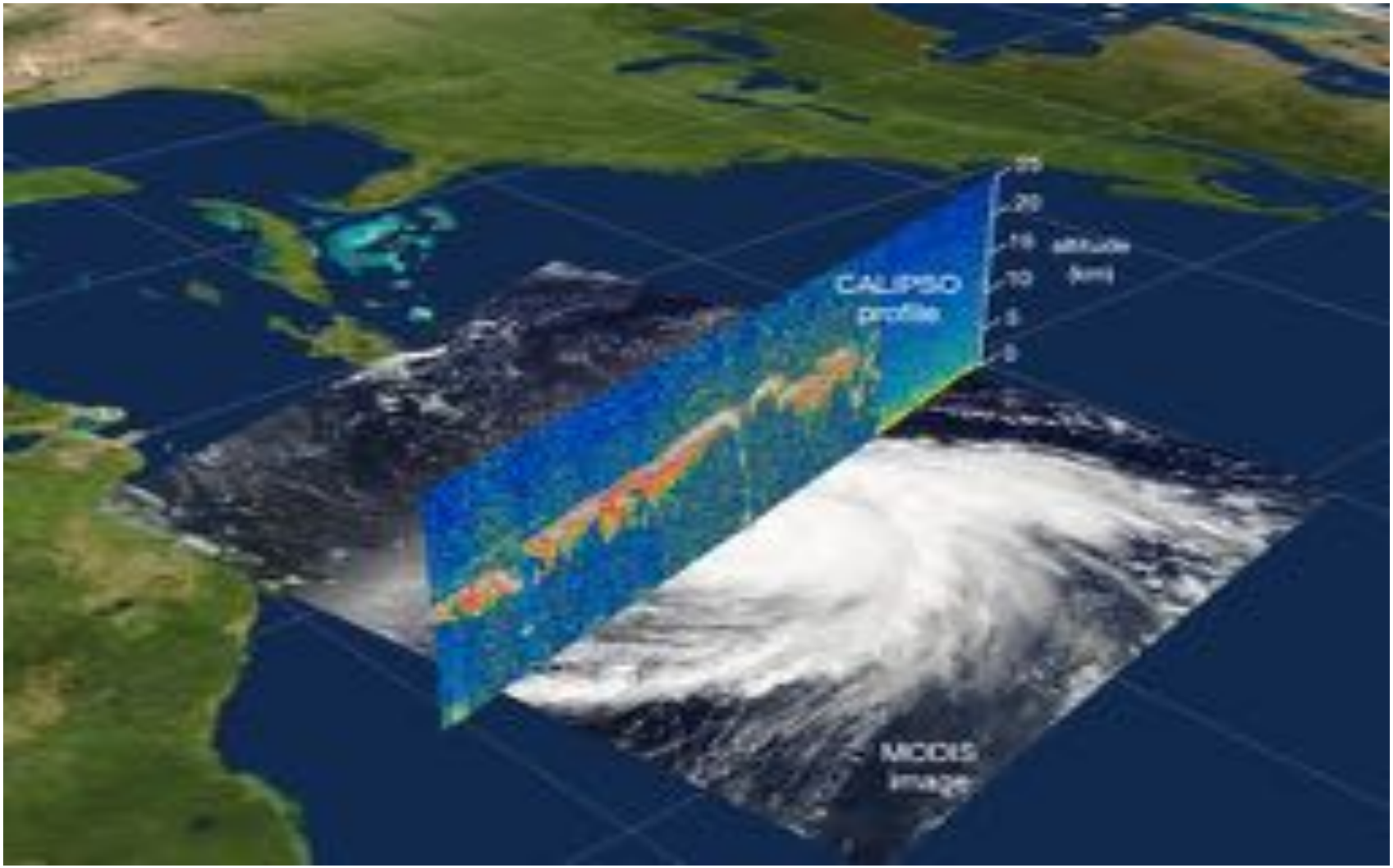
SCM cloud mask



MYD35 cloud mask



CALIOP collocated with Aqua MODIS



Validation using CALIOP observations as the benchmark

- Cloud-Aerosol Lidar with Orthogonal Polarization (**CALIOP**) is a lidar onboard the CALIPSO satellite that **provides high-resolution vertical profiles** of aerosols and clouds.
- Collocated Aqua MODIS/CALIOP data provide **the most reliable assessment** of cloud mask results by using CALIOP's active cloud detection scheme.
- MOD35 collection 6 product (MYD35 when using Aqua MODIS data) and CALIOP 1 km cloud layer product for the whole year of 2008 are used in the comparison.

Test criteria in the comparison

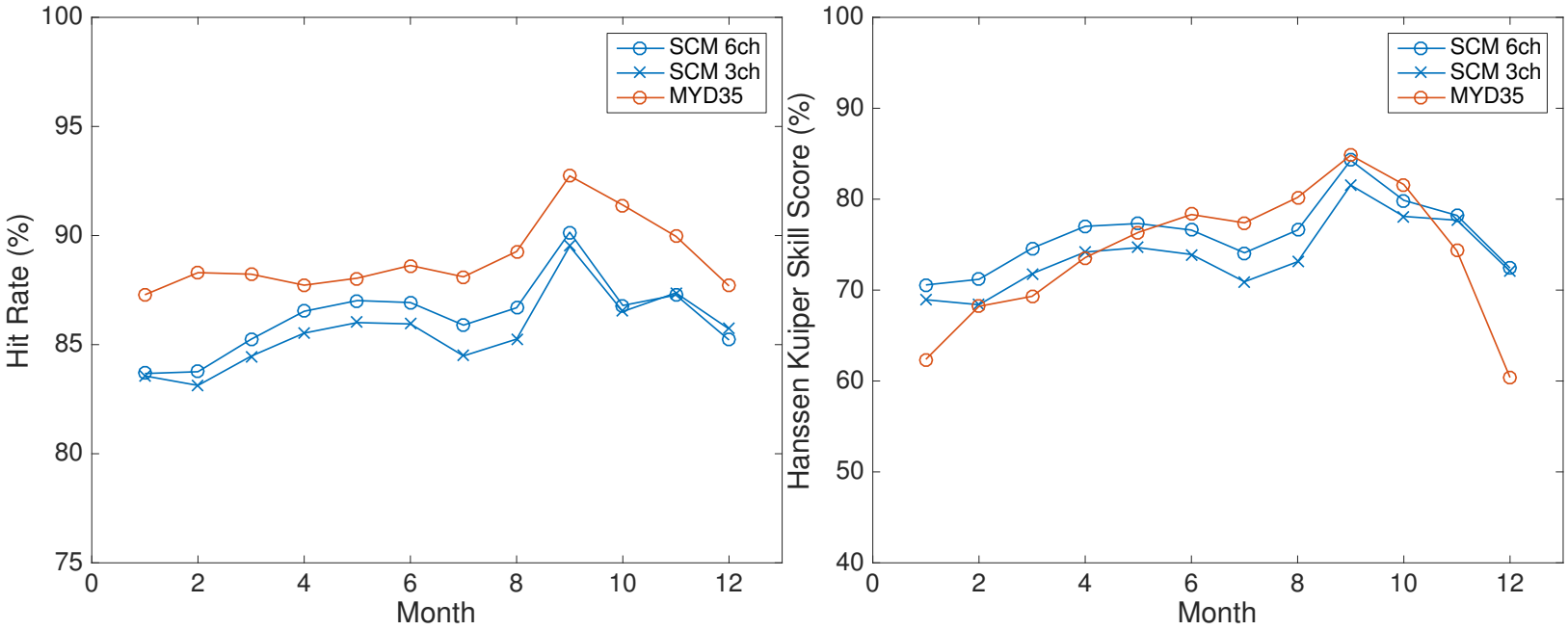
Hit Rate (HR)

$$\mathrm{HR} = \frac{N_{cld,hit} + N_{clr,hit}}{N_{total}} \quad (1)$$

Hanssen-Kuipers Skill Score or **True Skill Score (TSS)**

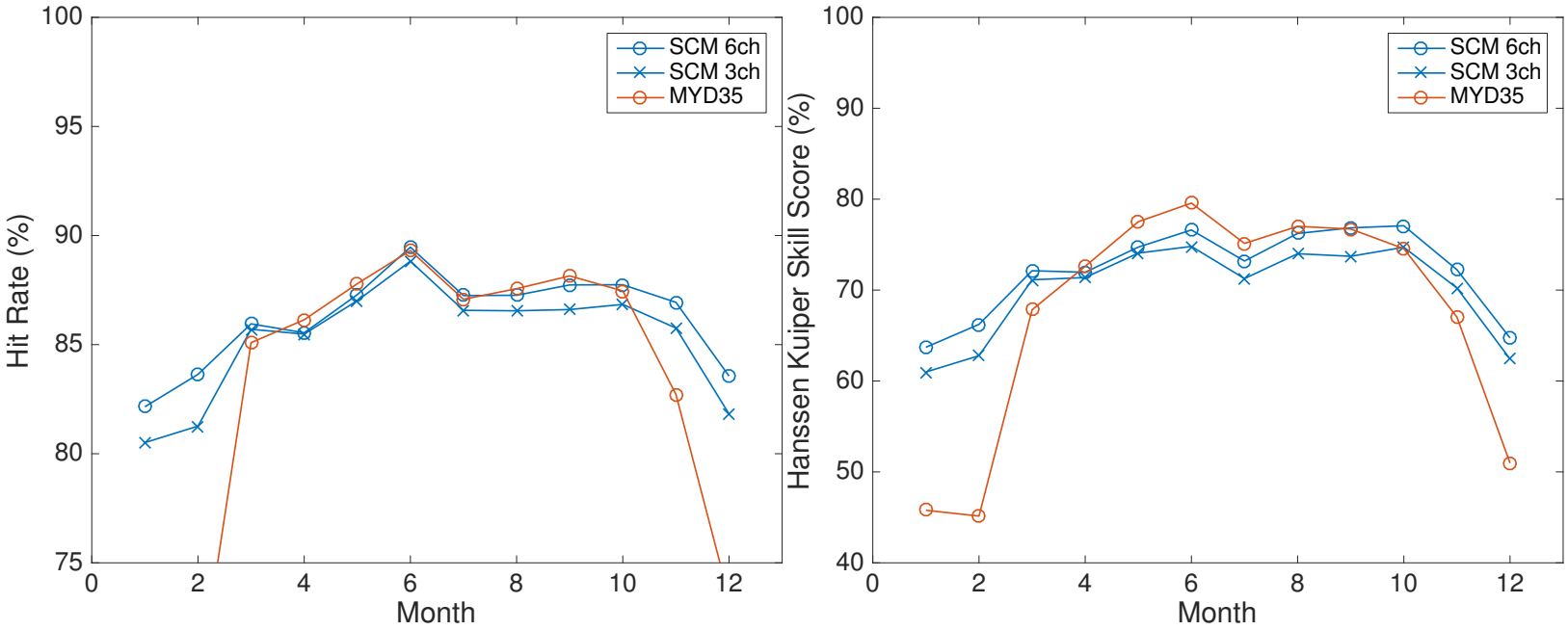
$$\mathrm{TSS} = \frac{(N_{cld,hit} \cdot N_{clr,hit} - N_{cld,miss} \cdot N_{clr,miss})}{(N_{cld,hit} + N_{cld,miss}) \cdot (N_{clr,hit} + N_{clr,miss})} \quad (2)$$

Test against MOD35 over mid-latitude region (Europe)



HR and TSS of our algorithm (SCM) and MOD35 (MYD35 for Aqua MODIS) over Europe for the year 2008.

Test against MOD35 over mid-latitude region (East Asia)



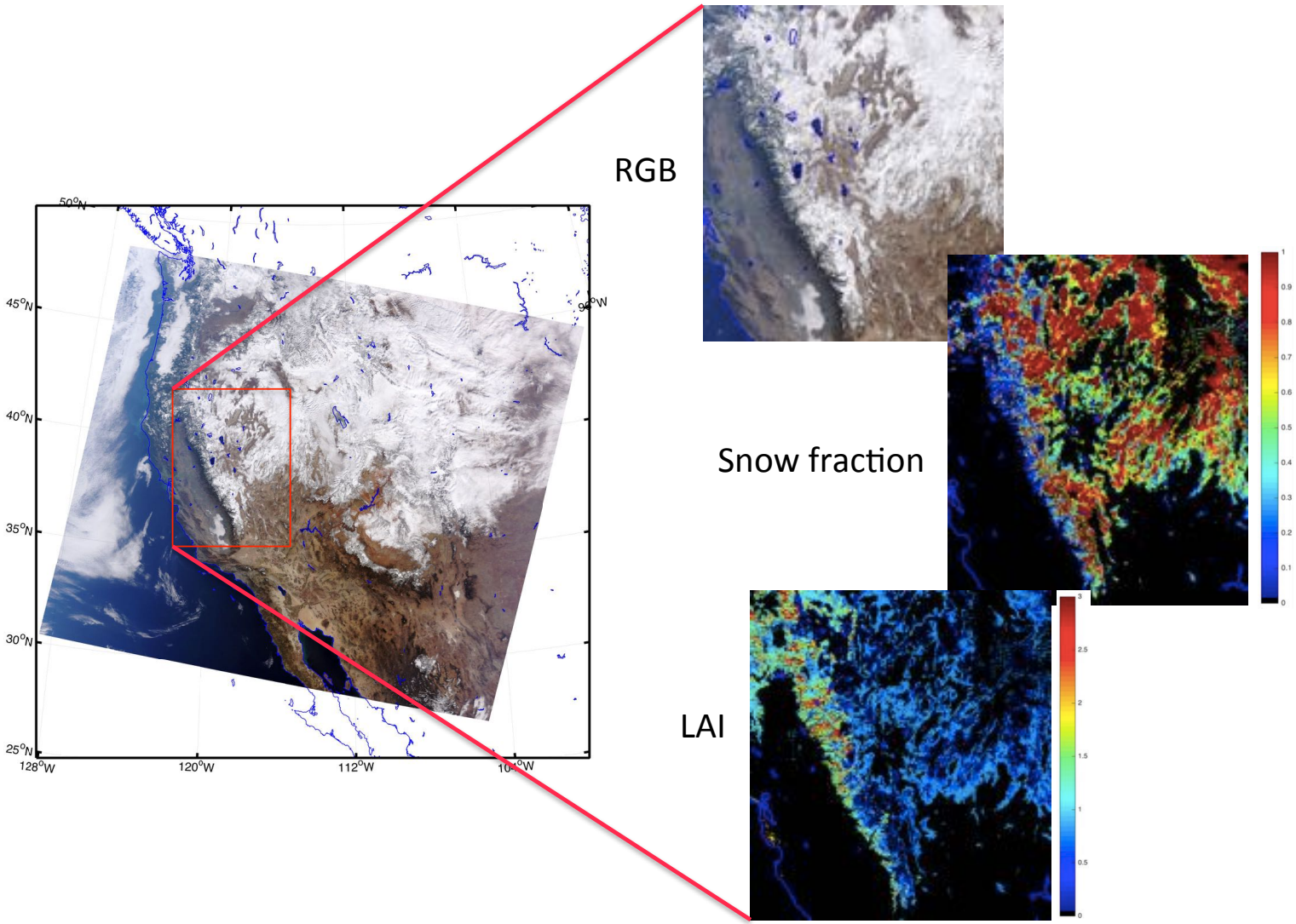
HR and TSS of our algorithm (SCM) and MOD35 (MYD35 for Aqua MODIS) over East Asia for the year 2008.

Snow detection

How about snow detection? Can we **detect snow without thresholds**?

- Use the same dataset in cloud mask training (only the clear-sky cases).
- A separate neural network is trained for estimation of **snow fraction** or other parameters such as **Leaf Area Index (LAI)**.
- Different vegetation types (green/brown) and soil types are included in the training dataset.

Results: snow fraction and LAI estimation



Summary

- The new algorithm, without any thresholds, **consistently performs cloud detection using fewer channels** than threshold-based methods.
- Its performance is **significantly better than MOD35** (with higher TSS throughout) in the winter seasons when the surface is partially (or fully) covered by snow.
- It can **easily be re-configured for other sensors** (e.g. AVHRR and/or Landsat) with similar performance.
- It can **estimate the snow fraction** for each pixel, which goes beyond the traditional binary NDSI snow detection.
- Other parameters like **LAI or fAPAR can also be estimated** in a similar manner.

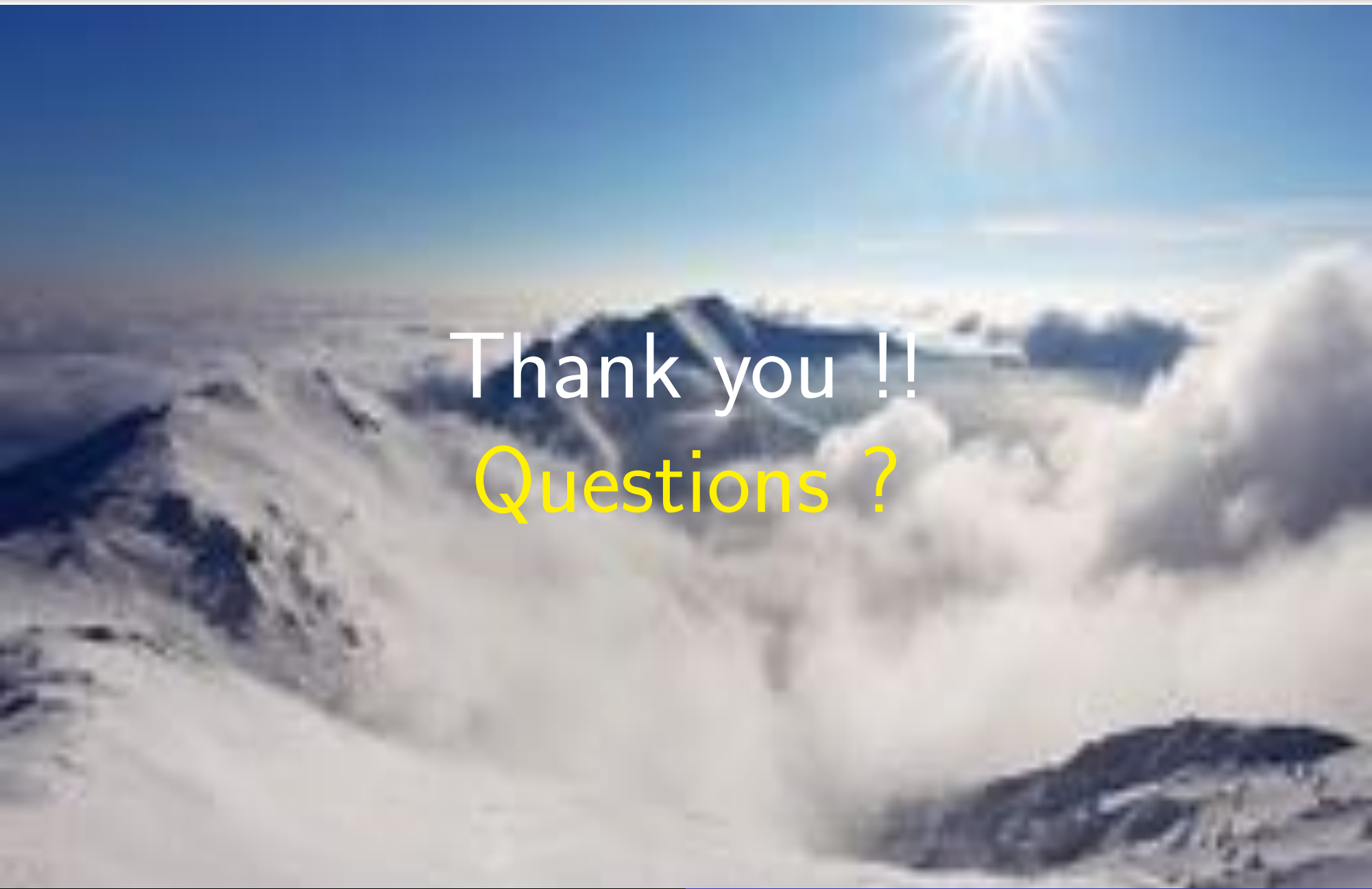

Thank you !!
Questions ?

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Image based result: vegetated land area

South America

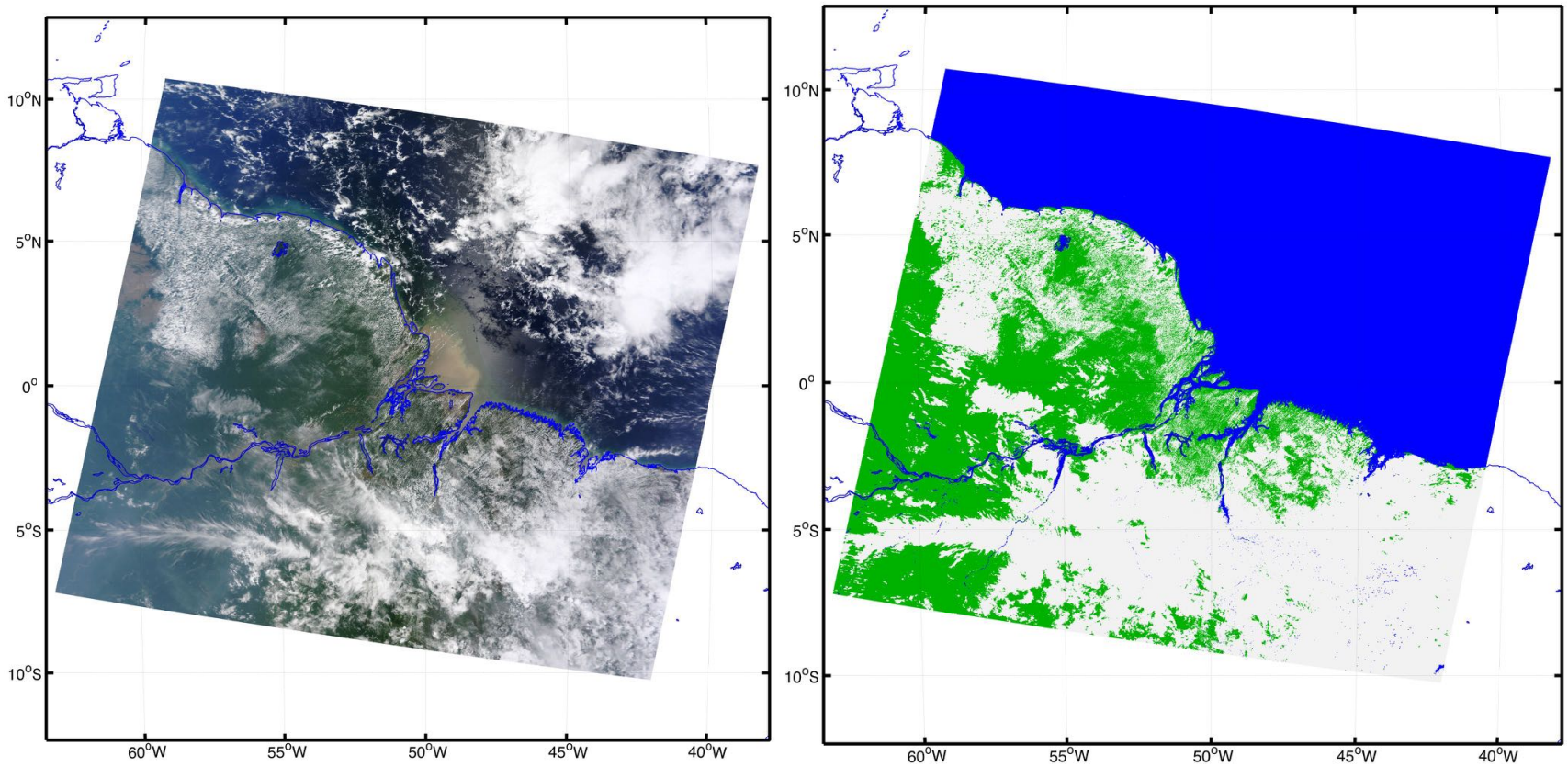


Image based result: desert area

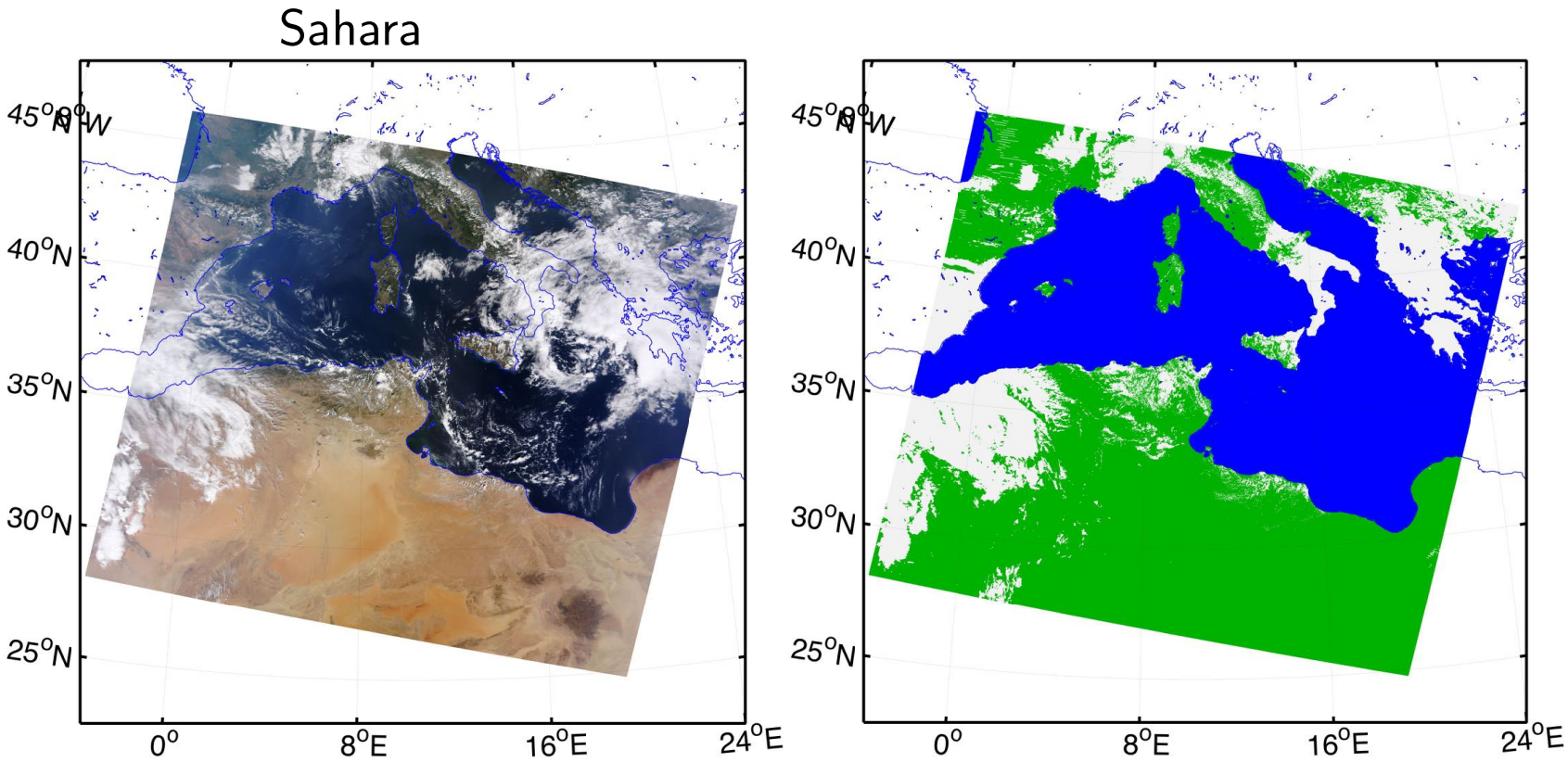
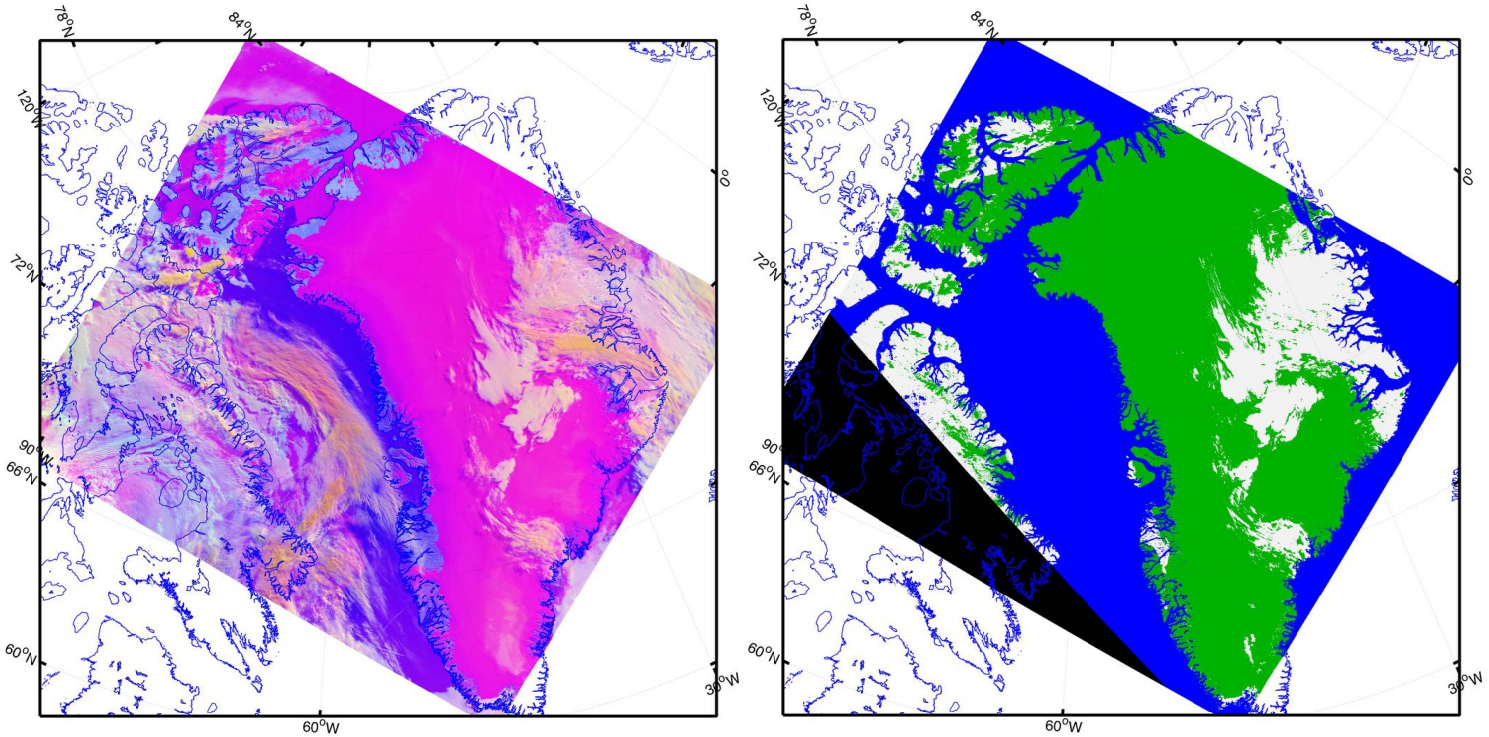


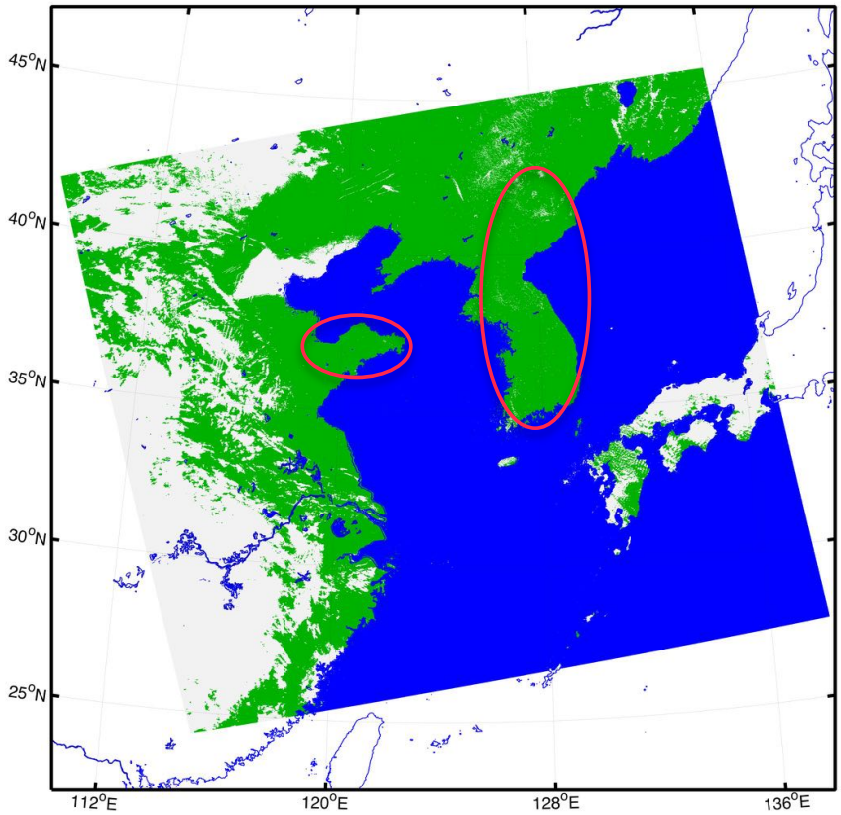
Image based results: snow-covered area



Comparison of cloud masks applied to an Aqua MODIS image over Greenland, Jul. 09, 2015. Left: False color RGB image; Right: SCM cloud mask. Color scheme of cloud mask figures: white/grey - clouds, blue - ocean, green - land.

Image based results: snow-mixed vegetation/soil area

SCM cloud mask



MYD35 cloud mask

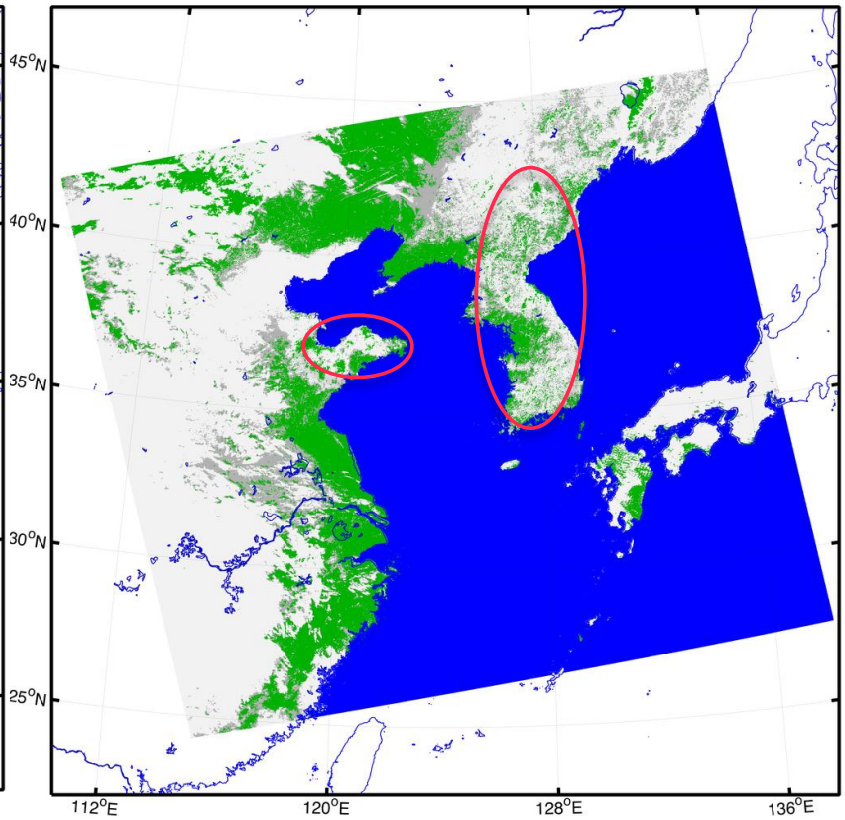
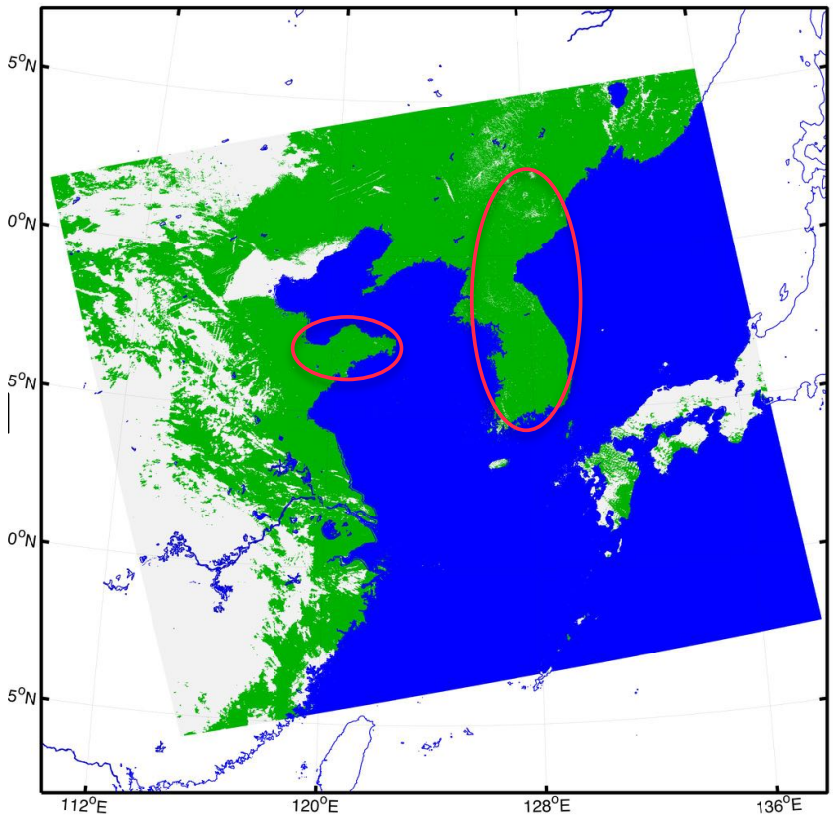


Image based results: snow-mixed vegetation/soil area

SCM cloud mask



MYD09 cloud mask